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ABSTRACT

This paper illustrates the differences in inference that can be seen when traditional and multilevel structural equation modeling techniques are applied to hierarchical data. Research on faculty is an area in which multilevel data exist, and where previous research generally has not modeled the nested structure. Using data from the National Study of Postsecondary Faculty (NSPOF), this paper demonstrates a method for analyzing data that contain measurement error and come from multilevel structures. The NSPOF database contains responses from 25,780 faculty randomly chosen from 817 participating institutions. The integration of multilevel regression modeling and structural equation modeling, which can facilitate proper inference, is used to study faculty satisfaction. In this study, no substantive differences were shown when traditional and more complex modeling techniques were compared, but the results from the analyses contribute to the knowledge base regarding the institutional and job characteristics that can affect faculty satisfaction. Two appendixes contain the NSPOF questionnaire and the EQS syntax for the "independence model." (Contains 2 tables, 7 figures, and 16 references.) (SLD)

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Using Multilevel Structural Equation Modeling with Faculty Data

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Using Multilevel Structural Equation Modeling with Faculty Data

Data used in higher education research often are multilevel (hierarchical) in structure, and commonly used statistical methods rarely model these structures appropriately. Using data on faculty satisfaction from the National Study of Postsecondary Faculty, the current paper illustrates the differences in inference that can be seen when applying traditional and multilevel structural equation modeling techniques to hierarchical data. The aim of this paper is to improve the theory and practice of research on faculty by illustrating one method for analyzing data which contain measurement error as well as come from multilevel structures. In addition, the data-related issues that must be addressed in any analysis that uses multilevel data are highlighted. Finally, the research adds to the body of work on institutional policies that can affect faculty satisfaction.

Problems when data are clustered

Research on faculty provides one area in which multilevel data exist and where previous research generally has not modeled the nested structure. National data on faculty opinions, likeliness to leave, and job conditions are available from the National Study of Postsecondary Faculty (NSOPF). However, these data, like many in research on higher education, were collected from individuals in nested structures – faculty nested in institutions. One of the fundamental assumptions of traditional statistical techniques such as ANOVA and multiple regression analysis is that data are obtained from independent observations, thus resulting in errors that are independent. With nested designs, this assumption is typically violated and the resulting groups of faculty will likely be characterized by some degree of homogeneity.

The assumption of independent observations is crucial for the estimation of standard errors of parameters (Lee, Forthofer, & Lorimor, 1989). Kish and Frankel (1974), in empirical studies of large samples, found that the parameter estimates themselves were fairly robust to violations of the assumption of independent observations, but they delineate the (sometimes drastic) underestimation of sample variance of the parameters that can occur using traditional analysis methods. The traditional formulas for standard errors in statistics textbooks and incorporated into most statistical computer programs are based on a simple random sampling (SRS) design (Lee et al., 1989). Because these formulas assume that the correlation of the error terms is zero, a researcher will underestimate the sample variance when using traditional analytic methods. This underestimate will result in narrower confidence intervals around parameter estimates and the researcher will reject the null hypothesis regarding that parameter more often than appropriate. In other words, the chance of making a Type I error when testing a specific parameter increases. Scariano and Davenport (1987) reported on a simulation study which estimated the Type I error rates under conditions of dependent clustering in ANOVA. As an example of their findings, with only modest levels of dependency and two means, the Type I error was .57 for group sizes of 100, far from the assumed nominal rate of .05. Naive analysis of nested data, therefore, may lead to the mispronouncement of statistically significant predictive relationships where only random covariation exists.

Beyond the misestimation of standard errors, it is quite possible that a researcher using a traditional statistical method is failing to model the appropriate relationship. As a simplistic example, suppose that it was of interest to study the relation between university faculty's reported "percent of time spent teaching" and the perceived satisfaction with "my job here, overall" as displayed in the figure below.

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Insert Figure 1 about here

Without taking the faculty member's institution into account, it appears that the less a faculty member teaches (proportionately), the greater the satisfaction with the job, as shown by the bold line. However, satisfaction with the job is likely related to institutional characteristics and therefore, a multilevel analysis is appropriate. Such an analysis would model the data as diagramed by the two thin lines in the figure (assuming for simplicity only two institutions). Note that the institutional-identification

allows the researcher to model the relation of time spent teaching to satisfaction within the institution. In this case, there appears to be no appreciable relation between time spent teaching and satisfaction within each institution. Most of the variance in time spent teaching is found between institutions, not within institutions. When the data are modeled in this way, it can also be seen that institutions with relatively high averages on percent of time spent teaching have relatively lower average ratings on satisfaction (as illustrated by the two institutions in this example). Inappropriately ascribing such group properties to the individual is termed an "individualistic" or "psychologistic" fallacy in the psychology literature (Diez-Roux, 1998). This two-institution example is certainly a simplistic situation, but the issues extend to the very real case when data are collected from faculty at hundreds of institutions.

Problems when measures contain error

An additional problem apparent in higher education research is the use of observed variables which contain measurement error when the interest is really in a latent construct. For example, when trying to understand the relation between student motivation to learn mathematics and success in mathematics (and eventual retention at the university), researchers might use just one item from a survey which asks students to indicate the degree to which they are motivated to learn mathematics. This measure may contain some measurement error, including error due to social desirability. The concept of "motivation," however, is really a latent construct, unable to be directly measured. It can be useful to use several measures regarding motivation and behavior to make more accurate inferences about the underlying construct of motivation to learn mathematics. Researchers of faculty satisfaction often do not frame their research questions in terms of constructs, where relevant, but in terms of the error-prone data elements that are available. A notable exception is provided by Hagedorn (1996) when she investigates wage equity and faculty satisfaction constructs.

A technique called multilevel structural equation modeling can be used to address these two issues of multilevel data and measurement error. Within the last few years, the use of structural equation modeling with multilevel data has begun to be addressed by researchers in some educational fields (Hox, 1994; Kaplan & Elliott, 1997; Muthén, 1994). However, the literature does not indicate the use of this method in higher education research contexts. Even the more well-established multilevel techniques, such as hierarchical linear modeling (Bryk & Raudenbush, 1992; Goldstein, 1995; Kreft & de Leeuw, 1998), are rarely found in research on colleges and universities.

Study Design

Because the multilevel and latent construct aspects of data are infrequently accommodated in analyses, the NSOPF database is used in this paper to illustrate how the results that are obtained using limited traditional methods, such as the ubiquitous multiple regression, can differ from the results obtained using multilevel structural equation modeling. The NSOPF database includes responses from 25,780 faculty randomly chosen from a sample of 817 participating institutions. This paper shows that an integration of relatively new methods (multilevel regression modeling and structural equation modeling) can be used to facilitate proper inference and illustrates how to accomplish modeling appropriately with these techniques.

Using the NSOPF data, an analysis of the determinants of faculty satisfaction, including intentions to leave, is undertaken using both multiple regression and multilevel structural equation modeling. The issue of faculty satisfaction is an important consideration for academic administrators. Although making projections of faculty supply and demand has been shown to be a difficult task, there is fear that "if the long-awaited transformation to a 'sellers market' materializes, raiding wars might intensify to lure established faculty members away from other institutions, and institutional loyalty might correspondingly diminish" (Schuster, 1995). Institutions of higher education, therefore, ought position themselves to be cognizant of the factors that would contribute to a faculty member's satisfaction and ultimate decision to leave the university. Scholars have identified several issues related to faculty satisfaction, such as personal, job, and institutional characteristics (Hagedorn, 1996;

Johnsrud & Heck, 1994; Norrell & Norrell, 1996; Smart, 1990). The job and institutional characteristics include those things often under the administration's control, such as benefits and working conditions, and therefore the possibility exists that these characteristics can be examined for possible policy change.

Of special interest in the modeling of job satisfaction within this research on faculty satisfaction is the measurement of the construct "satisfaction" itself. Many analysts in higher education research might solely use the item which measures perceived satisfaction with "my job here, overall." However, we contend that it is more appropriate to identify a latent construct and therefore, additional measured variables are used.

Description of the NSOPF Methodology

The 1992-93 NSOPF was collected using a two-stage sampling design (National Center for Education Statistics, 1997). The first-stage of sampling included 974 two- and four-year institutions from the 3,256 institutions in 15 strata, defined by institution type. The institutions in one stratum were selected with certainty (all institutions were sampled), and the remaining were selected proportionate to size within their respective stratum. Of the 974 institutions sampled, 817 agreed to participate by providing lists of faculty. Within each institution, 41 or 42 faculty were randomly selected, however there was oversampling of full-time female, black, Hispanic, and Asian/Pacific Islander faculty, as well as faculty in four specified humanities disciplines. Faculty received a questionnaire and an institutional administrator was asked to complete an institution-level questionnaire. The response rate to the faculty questionnaire was 87 percent.

Simple Example

Initially, we were interested to find variables in the NSOPF dataset that exhibited a strong degree of clustering, that would lead to inappropriate conclusions if modeled without controlling for the clustering. For this simple analysis, we examined full-time tenured and tenure-track faculty at public comprehensive institutions. Faculty responses to two questions were examined for their bivariate relationship:

a) percent of time spent doing research, and
b) the amount of agreement to the statement "at this institution, research is rewarded more than teaching."

It was hypothesized that faculty who spend relatively more of their time in research will be less likely to agree with the statement in b) above. Conversely, faculty who spend most of their time teaching were expected to agree with the statement in b) above. Using a simple (single-level) multiple regression, we found that there was no statistically-significant relation between these two variables. As researchers, we might come away from the data claiming that whether or not you do research does not have a bearing on whether you think your institution rewards research more than teaching. However, when we undertook a multilevel analysis (by partialling out the institution-level variance), we found that within institutions, there was a significant and negative relation between the variables (as hypothesized) but across institutions, the relationship was positive: institutions with higher average faculty time spent on research had higher average agreement to the statement in b) above. This relationship is modeled in Figure 2 below. The dots represent one faculty member and the circles around a group of dots indicate that these dots come from the same institution. The stars represent the mean of the two measures for each institution. Note that within institutions, there is a negative relation between the two variables. Across institutions, however, one can see that the institution means have a positive relation.

Insert Figure 2 about here

Once we could see that multilevel analyses were appropriate with NSOPF data, we moved to a more complicated analysis, involving several variables and a latent construct.

Example Variables of Interest

For this analysis, interest is in modeling the institutional components which affect faculty satisfaction. Therefore, we desired to find conditions or benefits of the university which might affect a faculty member's satisfaction level. As measures of satisfaction, the responses to NSOPF items 40i, 59g, and a scale from question 41 were used in the analysis. The full item wording from the faculty questionnaire for the selected items used in this analysis can be found in the appendix. Response to item 40i is a rating of satisfaction with the job overall (JOBSAT), item 59g is a rating of whether the faculty member would choose an academic career again (AGAIN), and item 41 represents the faculty member's likelihood of leaving the current job (LEAVE). Independent variables included three variables, that were scales composed by several items, and two direct item responses. The scales were 'satisfaction with research resources' (SATRES) comprised of items 34a, 34b, 34c, 34j, and 34l (ratings of lab/studio facilities, availability of research assistants, and library holdings), 'satisfaction with teaching resources' (SATTCH) measured by items 34h and 34g (ratings of classroom space and audio/visual equipment), and 'satisfaction with computing resources' (SATCMP) comprised of items 34d, 34e, and 34f (ratings of personal and mainframe computers and networks with other institutions). The two remaining item responses used as independent variables were 40a and 40f, the faculty member's satisfaction with his/her workload (SATWKL) and salary (SATSAL), respectively.

We restricted the analysis to full-time faculty with the rank of Assistant, Associate, or Full Professor in four-year institutions. Faculty from both public and private institutions were included. Under these parameters, our sample consisted of 8,967 faculty from 511 institutions. On average, there were 17.5 faculty per institution. Descriptive information, as well as additional information to be discussed, is available in Table 1 and Table 2.

Insert Table 1 about here

Insert Table 2 about here

Diagnosis of Multilevel Properties

When working with data collected from a two-stage sample, it is prudent for a researcher to first determine the amount of homogeneity within clusters as compared to the entire sample before proceeding to the analysis. If there is no within-group homogeneity, then a single-level analysis will not yield incorrect parameter variance estimates. The measure of within-group homogeneity is termed the coefficient of *intraclass correlation* (ICC), and is the correlation between all possible pairs of elements within clusters (Lee et al., 1989). The ICC ranges from $-1/(c-1)$ to 1 (where c is the common group size). If it is close to zero, it is an indication that the clustering effect is the same as would be found in a simple random sample. If the ICC is close to 1, however, it indicates that nearly all of the variance can be accounted for by the clustering.

One can estimate the intraclass correlation by calculating the total amount of variance in a particular variable that is accounted for by the between-group variance, and this can be accomplished by using parameters from an analysis of variance (ANOVA). The ICC can be estimated as:

$$ICC = (MS_B - MS_W)/(MS_B + [c-1]MS_W)$$

where MS_B is the mean square between (model)

MS_W is the mean square within (error)
c is a measure of group size, calculated as $(n^2 - \Sigma n_j^2)/[n(G-1)]$
where n is the total sample size and G is the number of groups and n_j indicates the size of the j^{th} group (Muthén, 1994).

Previous research indicates that with geographically-determined clusters, the intraclass correlation is relatively low on demographic variables (such as age and gender) and higher for socioeconomic variables and attitudes (Kalton, 1977). In educational studies, the intraclass correlations have been found to be rather high: between .3 and .4 due to classroom components when examining mathematics achievement for U.S. eighth graders (Muthén, 1996). Note again that if the ICC=0 or if only one element is sampled from each cluster then the parameter variance estimates are not biased. If the ICC=0, then one can safely ignore the sampling design, however, any departures of the ICC from zero should be treated carefully -- even a relatively small positive ICC can have a large effect on the variance, if the size of the clusters is large. For example, if there are 30 faculty in each institution and one of our variables is found to have a (very small) .05 ICC, the proper variance estimate would be more than two and one-half times the estimate one would get assuming simple random sampling. For more information on estimating the effect of positive ICCs, see the 'design effect' information in Lee et al. (1989).

We calculated the ICCs for the variables used in the analysis and they can be found in Table 1. We demonstrate below the calculation of the ICC for the variable, 'satisfaction with research resources' (SATRES). The following SAS syntax was used (note that PROC GLM was utilized for the ANOVA because we needed to include the observation weight, which was scaled to reflect the total sample size):

```
PROC GLM;
  CLASS INSTID;
  MODEL SATRES
        = INSTID;
  ;
  WEIGHT ADJWEIGHT;
RUN;
```

And it produced the following output:

```
Dependent Variable: SATRES

Weight: ADJWEIGHT
```

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	510	1063.993800	2.086262	5.52	<.0001
Error	8456	3193.755567	0.377691		
Corrected Total	8966	4257.749367			

Therefore, we can calculate the ICC as:

ICC = (2.086-0.378)/(2.086+[17.542-1]0.378) = 1.708/8.339 = .205

So just over 20 percent of the variance in SATRES can be accounted for by the institutional grouping. This makes intuitive sense; at relatively wealthy institutions, faculty are likely to indicate that they are satisfied with research resources, and the converse would be expected to hold for faculty at less wealthy institutions. Satisfaction with research and computer resources, as well as satisfaction with salary had the highest ICCs. Conversely, satisfaction with workload and our three dependent variables, which are indicators of the latent construct of satisfaction had lower ICCs.

Single-Level Model without Latent Constructs

A researcher unfamiliar with the issues of multilevel data and latent constructs might approach the issue of determining how institutional and job characteristics affect faculty satisfaction by using a multiple regression analysis. A single measure, perhaps satisfaction with the job overall, would be

regressed on the independent variables of satisfaction with various resources, salary, and workload. We undertook such an analysis, modeling as indicated in the formula below and in Figure 3.

$$SATJOB_i = \beta_0 + \beta_1 SATRES_i + \beta_2 SATTCH_i + \beta_3 SATCMP_i + \beta_4 SATWKL_i + \beta_5 SATSAL_i + \epsilon_i$$

Insert Figure 3 about here

From these standardized estimates (all of which are significant at α=.05), we would infer that job satisfaction overall is positively related to faculty members' satisfaction with their workload and their salary, followed by their satisfaction with research resources. To a lesser extent, their overall satisfaction is also related to their satisfaction with teaching resources and computing resources. This model exhibits an R^2 of 39.6%, indicating that just under 40% of the variance in JOBSAT is explained by these five independent variables.

Latent Construct

Realistically, one measure of job satisfaction (satisfaction with the job overall) will not be a perfectly reliable indication of true satisfaction; it will contain measurement error. Several measures regarding a faculty member's satisfaction would provide a more complete picture of the construct of satisfaction. For example, we would expect that a faculty member who is truly unhappy in her position would answer negatively to the item regarding overall satisfaction, answer positively about plans to leave, and negatively to the item about entering a position in academe again. We, therefore, hypothesized that a latent construct, which we will call "faculty satisfaction" (FACSAT), could be indicated by those three variables, JOBSAT, LEAVE, and AGAIN. A single-level confirmatory factor analysis shows the significant standardized loadings displayed in Figure 4. Per expectation, JOBSAT and AGAIN loaded positively on the construct, while LEAVE loaded negatively.

Insert Figure 4 about here

Multilevel Structural Equation Modeling

In this section, we will present the conceptual underpinnings of multilevel structural equation modeling (ML-SEM). Hox (1994) provides an excellent resource for researchers interested in a step-by-step process to undertake ML-SEM. Several software packages exist for SEM, such as EQS, AMOS, LISREL, and Mplus, and each of these can accommodate multilevel modeling.

The single-level model, as displayed in Figure 5, takes the total covariance matrix for the sample dataset and imposes a covariance structure per the model hypothesized. For each of the subsequent models, we will be hypothesizing that our latent construct of "faculty satisfaction" is affected by SATRES, SATTCH, SATCMP, SATWKL, and SATSAL. In addition, a direct path from SATWKL to LEAVE is modeled, indicating that satisfaction with workload affects intentions to leave, beyond that explained by the indirect effect through the latent factor. This path was added from post hoc tests and was not initially hypothesized. This single level model fits the data very well (CFI=.998 and RMSEA=.021) and suggests that all five measures of resource/benefit satisfaction positively affect faculty satisfaction. The standardized coefficients suggest that satisfaction with salary and workload have stronger effects (.381 and .340 respectively), while satisfaction with computer and teaching resources have weaker effects. The five independent variables explained approximately 50 percent of the variance in "faculty satisfaction." Also note that the standardized path from SATWKL to LEAVE was large and positive, .690, indicating a strong relationship between satisfaction with workload and intentions to leave the university for another full-time job. One possible theory to explain this path is

that it may reflect "upwardly-mobile" faculty who are in the beginning of their careers and feel successful with their workload now but also intend to "move up" to another institution.

Insert Figure 5 about here

If the researcher recognizes he multilevel nature of the data and wishes to model the relations within institutions, controlling for institutional effects, a more involved procedure should be undertaken. Instead of modeling the total covariance matrix, as demonstrated above in the single-level model, the analysis models both the pooled within-group covariance matrix (S_{PW}) and the between-group covariance matrix (S_B), where

$S_{PW} = [\Sigma (y_{ij} - y_j)^2] / (n-G)$ and

$S_B = [\Sigma n_j (y_j - y_.)^2] / (G-1)$.

Note that the S_{PW} is an unbiased estimate of the population pooled within covariance matrix, Σ_{PW}, however, S_B is an estimate of not only the population between-group covariance matrix, Σ_B, but of the Σ_{PW} as well. S_B is an estimate of ($\Sigma_{PW} + c\,\Sigma_B$) where c is the common group size (Graybill, 1961, p. 353-354; Muthén, 1994). Therefore, one cannot simply impose an individual-within-institution model on the S_{PW} and an institutional-level model on S_B. Instead, Muthén (1994) proposes to use a two-group analysis in traditional SEM software, modeling the sample between-group covariance matrix (S_B) using a between-group and within-group structure in the first "group." The second "group" analyzes the sample pooled-within covariance matrix (S_{PW}) and models the within-group structure alone. Additionally, constraints are imposed across the two analysis groups for every parameter in the within-group model. The EQS syntax for this model is located in the Appendix. Note that if the ICCs are zero for all variables in the analysis, the two covariance matrices would be equal ($S_{PW}=S_B$).

Hox (1994) proposes a four-step process to analyze multilevel data using SEM. First, he suggests that an analyst run a "null" model on the two covariance matrices. This model, depicted in Figure 6, imposes only the within-group model on both the S_{PW} and S_B and constrains all parameters to be the same across the two "groups." If this model fits, then it can be assumed that there was no or negligible between-group variance.

Insert Figure 6 about here

If this model is rejected (as ours was, with CFI=.767 and RMSEA= .090), it is an indication that between-group variance does, indeed, exist and should be added to the model. This introduces Hox's (1994) next step, the "independence" model.

At this step, the researcher adds in "factors" that act as the institution mean level of the variable at the between-group level, when modeling the S_B only (see Figure 7). Note that no institution "factors" exist when modeling S_{PW} and therefore constraints are not necessary on these parameters. Note also that the path from the institution "factor" to the individual level variable is set to 4.17, or the square root of c, the "average-like" group size (17.542). This path value is required to properly scale the institution "factor" variance (Hox, 1994; Muthén, 1994). We would expect this model to fit the data better because we know that our variables contain group-level variance (as demonstrated by the positive ICCs). In fact, our model fits quite well, with a CFI of .954 and RMSEA of .044, indicating that there is, indeed, group-level variance, but likely not strong relations at the group level. (For example, a relation at the group level would be: institutions with higher mean levels of satisfaction with salary have higher mean levels of overall job satisfaction).

Insert Figure 7 about here

If the independence model is rejected, Hox (1994) suggests that the "maximal" model, which posits covariance between all of the institution-mean "factors," be run. This model will examine the best possible fit. If this model holds, the researcher can then posit models to explain the between-group structure as he sees fit. Models hypothesizing between-group structures are then compared to the fit for the "maximal" model to find the most parsimonious model that still exhibits good fit (minimizing the degradation from the fit supplied by the "maximal" model).

Our final model, in this case, was the independence model: institution level variance existed, but there were no significant institution-level relations. Within institutions, the standardized path values from the independent variables to the "faculty satisfaction" factor were very similar to the single-level model, and the interpretations for the institutional administrator remain the same: overall faculty satisfaction is driven strongly by whether the faculty are satisfied with their workload and salary, and less strongly with research, teaching, and computer resources. Note that while the paths from the five independent variables to the latent construct remain similar to that found in the single-level model, the path from SATWKL to LEAVE has dropped drastically from .690 to .063. Partialling out group-level variance changed the nature of this path. Also note that after we partialled out the institution-level variance, we were able to explain slightly less of the within-group variance than with the single-level model (47 versus 50 percent) because the single-level analysis explicitly assumes that all variance in the latent construct is at the within-group level.

Similarly, the results from our multilevel structural equation model do not differ substantially from those obtained with the multiple regression. The JOBSAT variable loaded very heavily on the "faculty satisfaction" construct leading to little difference between modeling just JOBSAT as the dependent variable versus the construct. Also, the ICCs for these three dependent variables were fairly low.

Summary

Data used for analysis in higher education contexts often contain intricacies that are not accommodated in research analyses. Of principal interest in this investigation are the multilevel structure of data and the existence of measurement error in key observed variables, as they pertain to faculty issues. The database resulting from the National Study of Postsecondary Faculty has been used for the study of faculty and it also provides a unique opportunity to study problems of nested data, as well as to examine more appropriate methods to analyze data with these attributes. While no substantive differences were shown comparing traditional and more complex modeling techniques, this paper serves two important purposes. First, the results from the analyses contribute to the knowledge base regarding the institutional and job characteristics that can affect faculty satisfaction. Second, and most importantly, the paper educates researchers about multilevel data and the issues to be addressed when analyzing such data, which hopefully will result in improved practice in higher education research.

References

Bryk, A. S., & Raudenbush, S. W. (1992). Hierarchical linear models. Newbury Park, CA: Sage Publications, Inc.

Diez-Roux, A. V. (1998). Bringing context back into epidemiology: Variables and fallacies in multilevel analysis. American Journal of Public Health, 88(2), 216-222.

Goldstein, H. (1995). Multilevel statistical models. London: Edward Arnold, and New York: Halsted Press.

Hagedorn, L. S. (1996). Wage equity and female faculty job satisfaction: the role of wage differentials in a job satisfaction causal model. Research in Higher Education, 37(5), 569-598.

Hox, J. J. (1994). Applied multilevel analysis. Amsterdam: TT-Publikaties.

Johnsrud, L. K., & Heck, R. H. (1994). A university's faculty: Identifying who will leave and who will stay. Journal for Higher Education Management, 10(1), 71-84.

Kaplan, D., & Elliott, P. R. (1997). A didactic example of multilevel structural equation modeling applicable to the study of organizations. Structural Equation Modeling, 4(1), 1-24.

Kish, L., & Frankel, M. R. (1974). Inference from complex samples. Journal of the Royal Statistical Society, 36 (Series B), 1-37.

Kreft, I. G. G., & de Leeuw, J. (1994). The gender gap in earnings. Sociological Methods & Research, 22(3), 319-341.

Lee, E. S., Forthofer, R. N., & Lorimor, R. J. (1989). Analyzing complex survey data. Newbury Park, CA: Sage Publications, Inc.

Muthén, B. O. (1994). Multilevel covariance structure analysis. Sociological Methods & Research, 22(3), 376-398.

National Center for Education Statistics (1997). 1993 National study of postsecondary faculty methodology report, NCES 97-467. U.S. Department of Education: Washington, D.C.

Norrell, J. E., & Norrell, T. H. (1996). Faculty and family policies in higher education. Journal of Family Issues, 17(2), 204-226.

Scariano, S. M., & Davenport, J. M. (1987). The effects of violations of independence assumptions in the one-way ANOVA. The American Statistician, 41(2), 123-129.

Schuster, J. H. (1995). Whither the faculty? The changing academic labor market. Educational Record, 76(4), 28-33.

Smart, J. C. (1990). A causal model of faculty turnover intentions. Research in Higher Education, 31(5), 405-424.

Table 1

Variable	Mean	Std. Dev.	ICC
SATRES	2.670	0.689	0.205
SATTCH	2.858	0.655	0.080
SATCMP	3.038	0.709	0.164
SATSAL	2.522	0.963	0.127
SATWKL	2.855	0.921	0.054
JOBSAT	3.157	0.772	0.063
LEAVE	2.778	0.998	0.041
AGAIN	3.499	0.794	0.019

Table 2 – Total, Pool-Within, and Between-Group Covariance Matrices

Variable	SATRES	SATTCH	SATCMP	SATSAL	SATWKL	JOBSAT	LEAVE	AGAIN
Total Covariance Matrix								
SATRES	0.4749							
SATTCH	0.1960	0.4286						
SATCMP	0.2209	0.1608	0.5021					
SATSAL	0.2171	0.1341	0.1428	0.9265				
SATWKL	0.1849	0.1277	0.1273	0.3019	0.8488			
JOBSAT	0.2015	0.1390	0.1420	0.3606	0.3572	0.5965		
LEAVE	-0.1055	-0.0788	-0.0821	-0.2087	0.1964	-0.3018	0.9959	
AGAIN	0.0879	0.0689	0.0622	0.1634	0.1519	0.2217	-0.1872	0.6311
Pooled-Within Covariance Matrix								
SATRES	0.3777							
SATTCH	0.1676	0.3943						
SATCMP	0.1678	0.1469	0.4197					
SATSAL	0.1586	0.1080	0.1074	0.8088				
SATWKL	0.1443	0.1156	0.1038	0.2740	0.8031			
JOBSAT	0.1625	0.1190	0.1202	0.3159	0.3327	0.5590		
LEAVE	-0.1020	-0.0687	-0.0781	-0.1851	-0.1923	-0.2799	0.9554	
AGAIN	0.0782	0.0614	0.0579	0.1455	0.1456	0.2070	-0.1730	0.6189
Between-Group Covariance Matrix								
SATRES	2.0863							
SATTCH	0.6677	0.9974						
SATCMP	1.1013	0.3915	1.8674					
SATSAL	1.1877	0.5666	0.7301	2.8782				
SATWKL	0.8587	0.3279	0.5167	0.7659	1.6077			
JOBSAT	0.8479	0.4702	0.5046	1.1013	0.7627	1.2195		
LEAVE	-0.1639	-0.2471	-0.1491	-0.6000	0.2652	-0.6656	1.6683	
AGAIN	0.2500	0.1928	0.1339	0.4606	0.2556	0.1656	-0.4226	0.8335

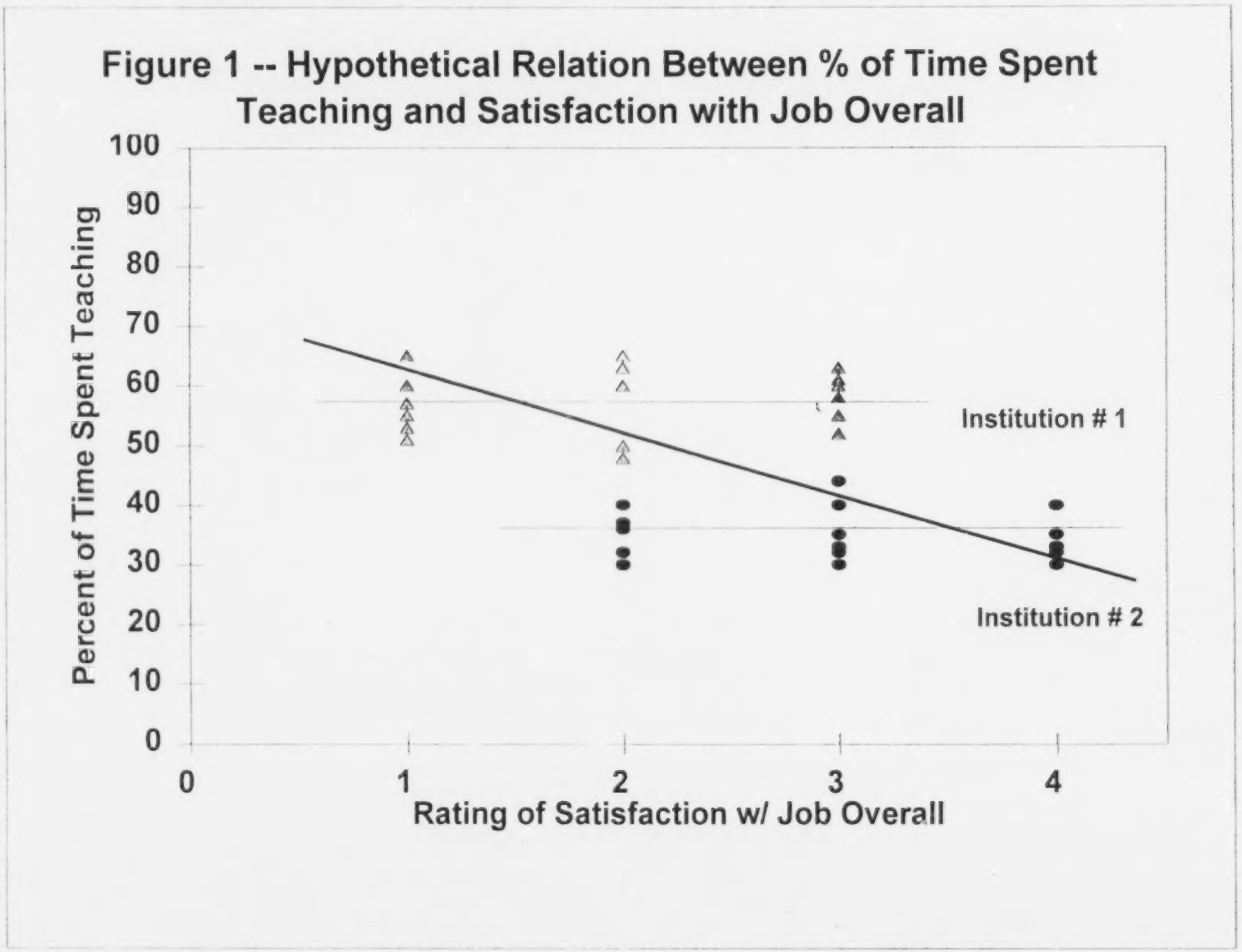


Figure 1 -- Hypothetical Relation Between % of Time Spent Teaching and Satisfaction with Job Overall
Percent of Time Spent Teaching
100
90
80
70
60
50
40
30
20
10
0
0
1
2
3
4
Rating of Satisfaction w/ Job Overall
Institution # 1
Institution # 2

Figure 2 -- Example graph of within and between relation

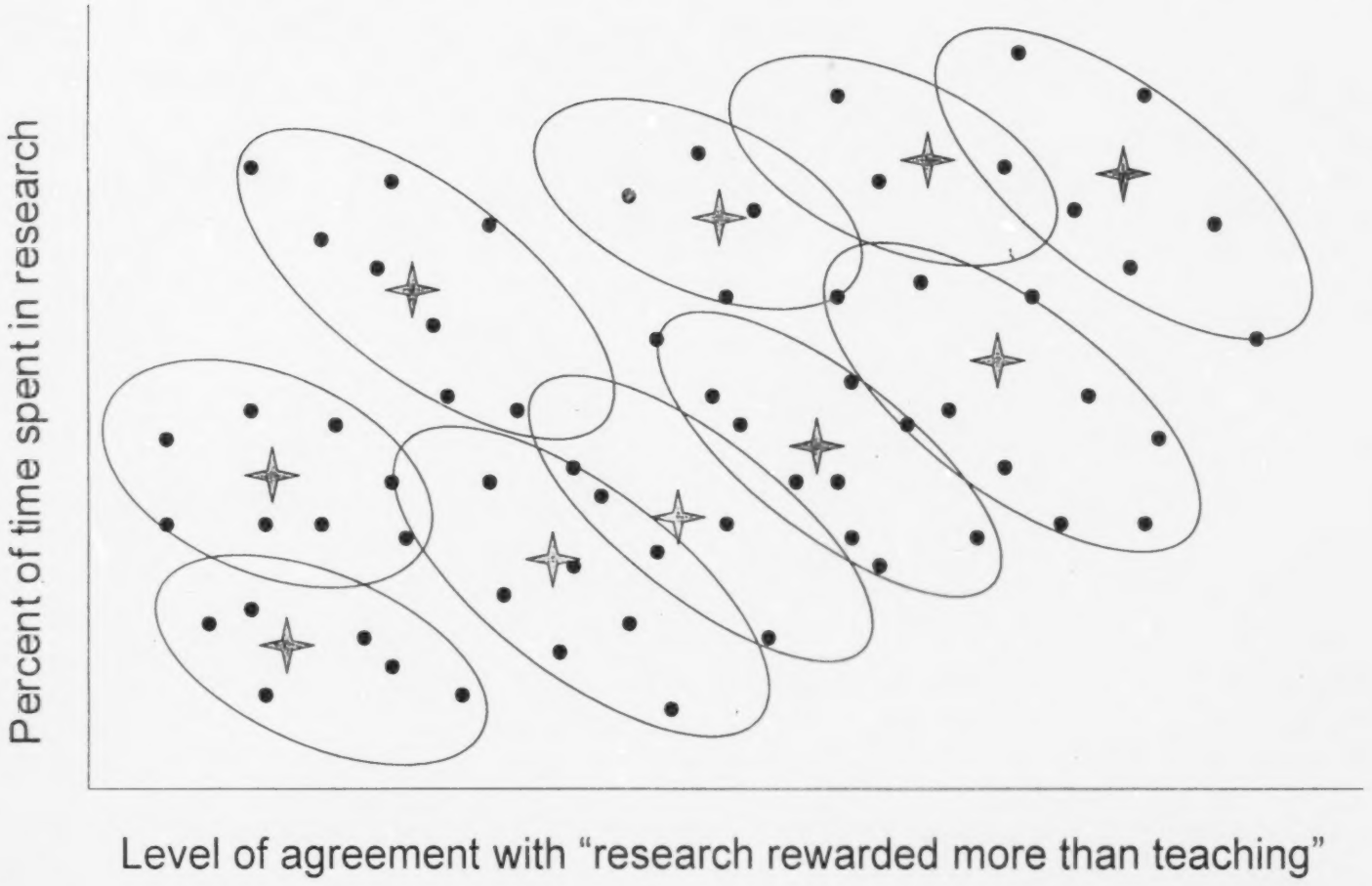


Figure 3 -- A single-level multiple regression model

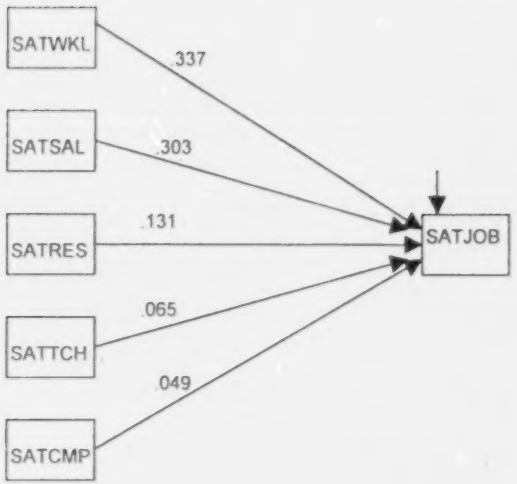


Figure 4 -- Single-level confirmatory factor model

Modeling the S_{TOTAL}

Figure 5 -- The single-level model

Modeling the S_{TOTAL}

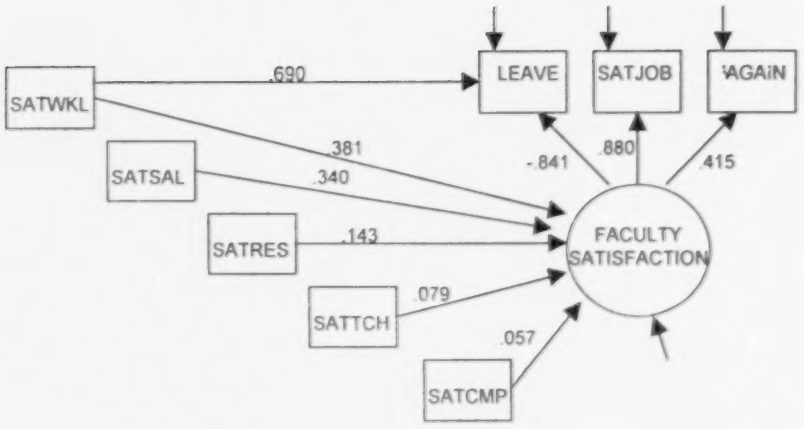


Figure 6 -- The "null" model

Modeling the S_{PW}

Modeling the S_B

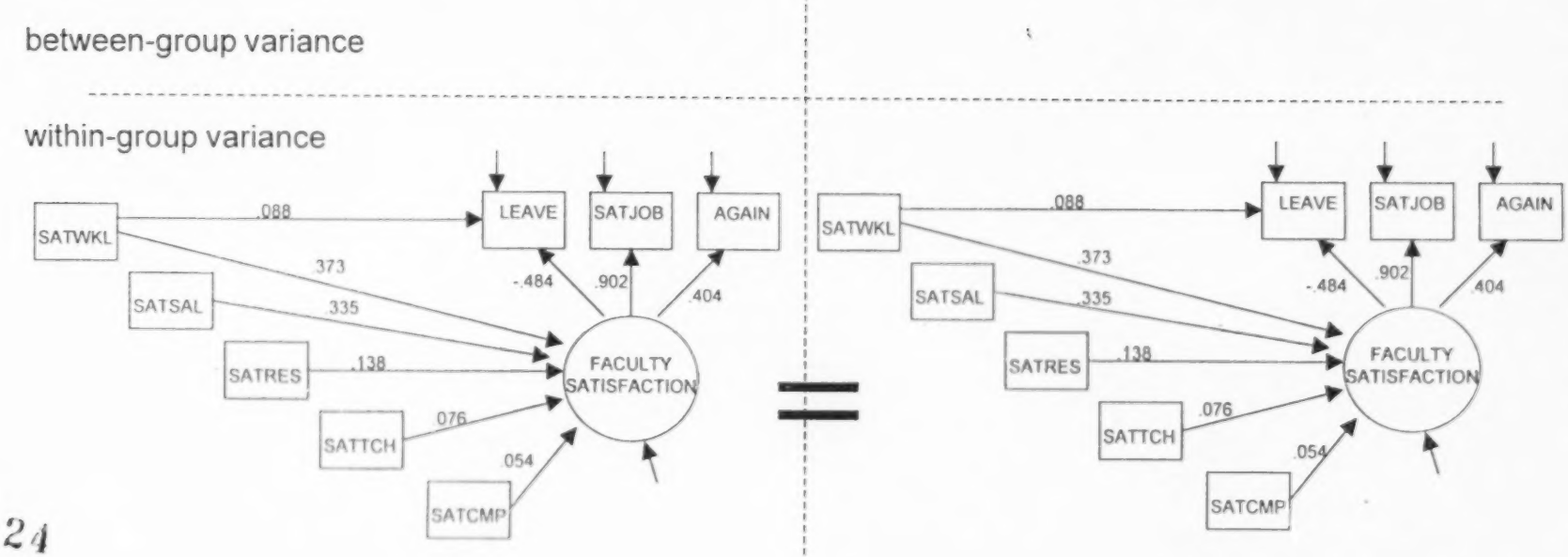
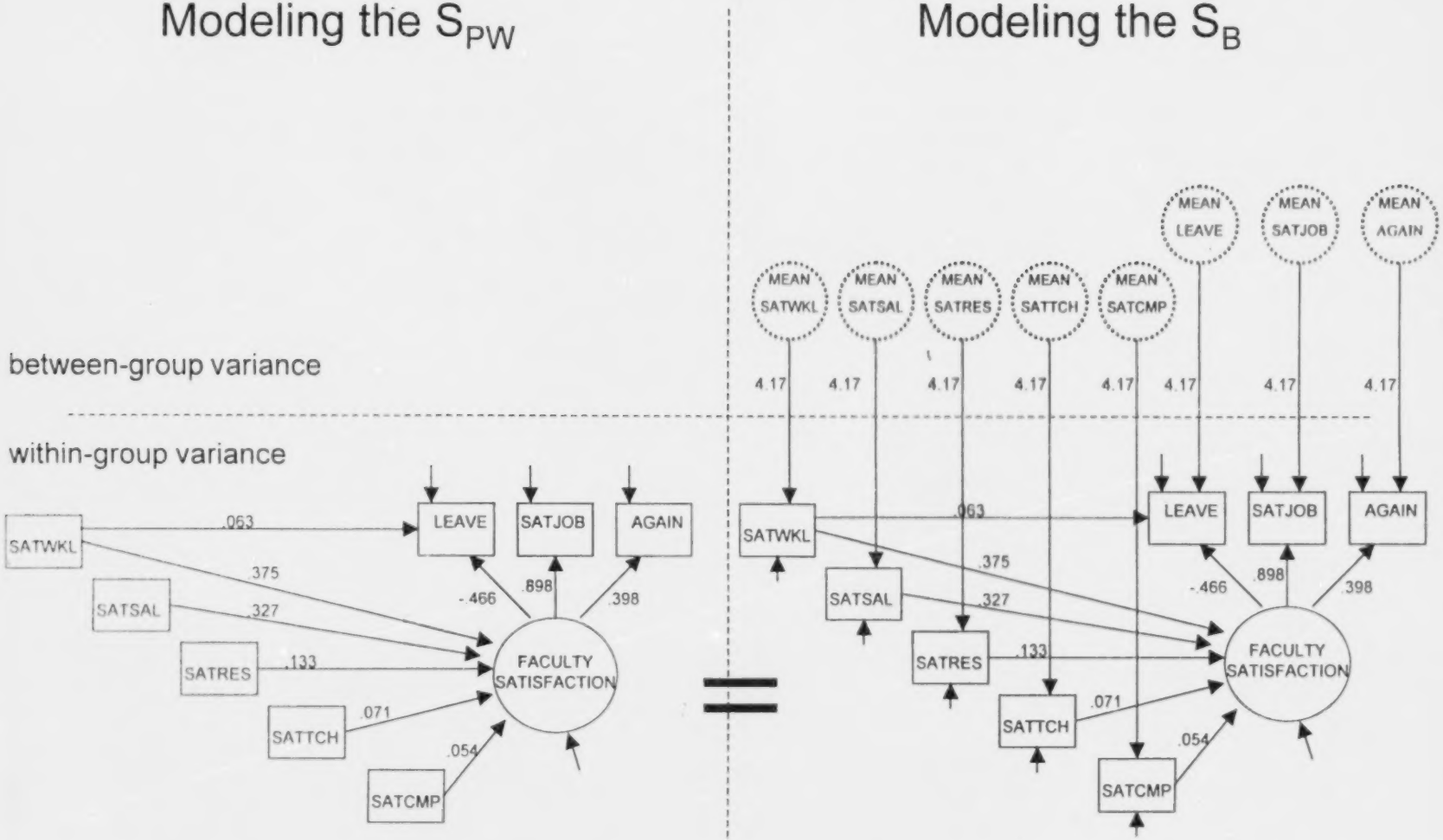


Figure 7 -- The "independence" model



Appendix

National Study of Postsecondary Faculty Questionnaire (Selected Items)

34. How would you rate each of the following facilities or resources at this institution that were available for your own use during the 1992 Fall Term? *(Possible responses are Not Applicable/Not Available, Very Poor, Poor, Good, and Very Good.)*

a. Basic research equipment/instruments
b. Laboratory space and supplies
c. Availability of research assistants
d. Personal computers
e. Centralized (main frame) computer facilities
f. Computer networks with other institutions
g. Audio-visual equipment
h. Classroom space
j. Studio/performance space
l. Library holdings

40. How satisfied or dissatisfied are you with the following aspects of your job at this institution? *(Possible responses are Very Dissatisfied, Somewhat Dissatisfied, Somewhat Satisfied, and Very Satisfied.)*

a. My workload
f. My salary
i. My job here, overall

41. During the next three years, how likely is it that you will leave this job to... *(Possible responses are Not At All Likely, Somewhat Likely, and Very Likely)*

b. accept a <u>full-time</u> job at a different postsecondary institution?
d. accept a <u>full-time</u> job <u>not</u> at a postsecondary institution?

59. Please indicate the extent to which you agree or disagree with each of the following statements. *(Possible responses are Disagree Strongly, Disagree Somewhat, Agree Somewhat, and Agree Strongly.)*

g. If I had it to do over again, I would still choose an academic career.

Appendix – EQS Syntax for 'Independence' Model

```
/TITLE
  AERA 2000 -- HOX'S INDEPENDENCE MODEL
 /SPECIFICATIONS
  CASES=511; VARIABLES=9; MATRIX=COV; GROUPS=2;
 /EQUATIONS
  V6= 4.19F6 + *V5 + *F9 + E6;
  V7= 4.19F7 + *F9 + E7;
  V8= 4.19F8 + 1F9 + E8;
  F9= *V1 + *V2 + *V3 + *V4 + *V5 + D9;
  V1= 4.19F1 + E1;
  V2= 4.19F2 + E2;
  V3= 4.19F3 + E3;
  V4= 4.19F4 + E4;
  V5= 4.19F5 + E5;
/VARIANCES
  F1 TO F8=*;
  D9=*;
  E1 TO E8=*;
/COVARIANCES
  E1,E2=*;
  E1,E3=*;
  E2,E3=*;
  E1,E4=*;
  E2,E4=*;
  E3,E4=*;
  E1,E5=*;
  E2,E5=*;
  E3,E5=*;
  E4,E5=*;
 /MATRIX
2.0863
0.6677      0.9974
1.1013      0.3915      1.8674
1.1877      0.5666      0.7301      2.8782
0.8587      0.3279      0.5167      0.7659   1.6077
-0.1639     -0.2471     -0.1491     -0.6000   0.2652   1.6683
0.8479      0.4702      0.5046      1.1013   0.7627   -0.6656   1.2195
0.2500      0.1928      0.1339      0.4606   0.2556   -0.4226   0.4656  0.8335
 /TECHNICAL
  ITR=500;
 /PRINT
  FIT=ALL;
 /END
/TITLE
  AERA 2000 -- HOX'S INDEPENDENCE MODEL
 /SPECIFICATIONS
  CASES=8456; VARIABLES=9; MATRIX=COV;
 /EQUATIONS
  V6= *F9 + *V5 + E6;
  V7= *F9 + E7;
  V8= 1F9 + E8;
  F9= *V1 + *V2 + *V3 + *V4 + *V5 + D9;
/VARIANCES
  D9=*;
  E6 TO E8=*;
  V1 TO V5=*;
/COVARIANCES
```

```
  V1,V2=*;
  V1,V3=*;
  V2,V3=*;
  V1,V4=*;
  V2,V4=*;
  V3,V4=*;
  V1,V5=*;
  V2,V5=*;
  V3,V5=*;
  V4,V5=*;
 /MATRIX
0.3777
0.1676      0.3943
0.1678      0.1469      0.4197
0.1586      0.1080      0.1074      0.8088
0.1443      0.1156      0.1038      0.2740    0.8031
-0.1020     -0.0687     -0.0781     -0.1851   -0.1928    0.9554
0.1625      0.1190      0.1202      0.3159    0.3327    -0.2799    0.5590
0.0782      0.0614      0.0579      0.1455    0.1456    -0.1730    0.2070   0.6189
 /TECHNICAL
  ITR=500;
 /CONSTRAINTS
  (1,V6,F9)=(2,V6,F9);
  (1,V7,F9)=(2,V7,F9);
  (1,F9,V1)=(2,F9,V1);
  (1,F9,V2)=(2,F9,V2);
  (1,F9,V3)=(2,F9,V3);
  (1,F9,V4)=(2,F9,V4);
  (1,F9,V5)=(2,F9,V5);
  (1,E1,E1)=(2,V1,V1);
  (1,E2,E2)=(2,V2,V2);
  (1,E3,E3)=(2,V3,V3);
  (1,E4,E4)=(2,V4,V4);
  (1,E5,E5)=(2,V5,V5);
  (1,E6,E6)=(2,E6,E6);
  (1,E7,E7)=(2,E7,E7);
  (1,E8,E8)=(2,E8,E8);
  (1,D9,D9)=(2,D9,D9);
  (1,E1,E2)=(2,V1,V2);
  (1,E1,E3)=(2,V1,V3);
  (1,E2,E3)=(2,V1,V3);
  (1,E1,E4)=(2,V1,V4);
  (1,E2,E4)=(2,V2,V4);
  (1,E3,E4)=(2,V3,V4);
  (1,V6,V5)=(2,V6,V5);
  (1,E1,E5)=(2,V1,V5);
  (1,E2,E5)=(2,V2,V5);
  (1,E3,E5)=(2,V3,V5);
  (1,E4,E5)=(2,V4,V5);
 /PRINT
  FIT=ALL;
 /END
/END
```